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Evaluation of How Public Disgrace Affects Instagram Influencers' Personal Brand Sentiment

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Abstract

The purpose of this paper is to examine how a public, negative incident (public disgrace) affects the general sentiment of Instagram influencers with respect to an influencer's following size. The proposed theoretical model, a quasi-experiment, consists of the sentiment score as the dependent variable, timing of the incident (pre or post), following size (high or moderate), and whether the influencer faced the incident or not as the independent variables. The approach is to identify the sentiments for the comments scraped per influencer analyzed and assess if there is a significant difference in average comment sentiment between following sizes. After a difference in differences analysis, the results indicate that an influencer with a high following is more adversely affected by a public, negative incident than an influencer with a moderate following. Both managerial and commercial implications for Instagram influencer marketing are provided. The findings demonstrate that influencers who face public, negative incidents can have significant repercussions for the brands involved.

Keywords

influencer, social media marketing, Instagram, public disgrace, social presence

Disciplines

Marketing

EVALUATION OF HOW PUBLIC DISGRACE AFFECTS INSTAGRAM INFLUENCERS' PERSONAL BRAND SENTIMENT

By

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An Undergraduate Thesis submitted in partial fulfillment of the requirements for the

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ABSTRACT

The purpose of this paper is to examine how a public, negative incident (public disgrace) affects the general sentiment of Instagram influencers with respect to an influencer's following size. The proposed theoretical model, a quasi-experiment, consists of the sentiment score as the dependent variable, timing of the incident (pre or post), following size (high or moderate), and whether the influencer faced the incident or not as the independent variables. The approach is to identify the sentiments for the comments scraped per influencer analyzed and assess if there is a significant difference in average comment sentiment between following sizes. After a difference in differences analysis, the results indicate that an influencer with a high following is more adversely affected by a public, negative incident than an influencer with a moderate following. Both managerial and commercial implications for Instagram influencer marketing are provided. The findings demonstrate that influencers who face public, negative incidents can have significant repercussions for the brands involved.

Keywords: influencer, social media marketing, Instagram, public disgrace, social presence

EXECUTIVE SUMMARY

Sourcing the right influencers for a marketing campaign/promotional effort can pose a challenge for many brands especially if some of these influencers face public, negative incidents. This paper investigates how in the event of a public, negative incident, the general sentiment of influencers changes relative to following size. Based on accepted social media marketing practices, I identified two salient following size groups: influencers who have a following of at least 1,000,000, and influencers who have a following between 100,000 and 1,000,000. To test for changes in general sentiment, I devised a quasi-experiment where I evaluated the sentiment of Instagram comments pre-incident and post-incident for each following group. I found in the event of a public, negative incident, influencers with a following of at least 1,000,000, face a more significant downturn in general sentiment than those influencers who have a moderate-sized following. A feasible, commercial application of this finding suggests that brands should consistently and continuously vet influencers who are involved in existing partnerships to ensure that the influencer's negative sentiment does not spill over into the brand's image & perception. Additionally, in the event of public disgrace, brands should actively request those influencers to give consistent updates and should monitor how these influencers address the incidents in their conversations with their followers. One suggested method would be to analyze the sentiment of comments post-incident up to at least a week after the incident has happened to ensure the viability of a continued influencer-brand partnership.

INTRODUCTION

The use of influencers to endorse products and services has been integral to brands' marketing strategies in recent years. Global spend on influencer marketing is predicted to be worth $2.38 billion (Statista). While overall spending has increased, 67.6% of marketers consider finding relevant influencers their largest influencer marketing challenge (99firms). Literature in personal branding & self-branding finds that because of influencers, the online media space has increasingly become a profitable and cost-effective way for brands to capitalize on promotion and advertising.

Previous studies I discuss later have examined the impact of celebrity endorsements, specifically how a public, negative incident can affect the perception of the product or service endorsed by the celebrity. These studies find that the impact of public disgrace depends on the strength of the celebrity-brand association and the degree of consumer commitment to the brand.

However, there is little to no investigation into how public, negative incidents can affect influencer endorsements. Generally speaking, studies into celebrity endorsements are used as predictors for how certain circumstances will affect influencer endorsements, but the celebrity studies are not generalizable. The difference between an influencer endorsement and celebrity endorsement is significant because an influencer is an ordinary person who creates content within a specific niche such as beauty, fashion, lifestyle, etc., or across several niches. The influencer's fame and presence in the online media are solely based on content created within those niches whereas niche content is tangential to a celebrity's fame. Whereas celebrity endorsements are designed to be aspirational, the appeal of influencer endorsements is that they are designed to be relatable, entirely user-generated, and personable. To explore this effect, my research specifically examines a popular social media platform, Instagram, where many influencers post niche-specific content in the form of photos, short-form videos, or both.

THEORETICAL FRAMEWORKS

The Appeal of Instagram Influencers

In recent years, influencer marketing has been deployed as a method of promoting a brand's product through employing 'ordinary people', that is people who build their social media presence around a specific niche, e.g. fashion, beauty, lifestyle, etc. The prevalence of influencer marketing is demonstrated by the fact that "75 percent of marketers are using influencer marketing" (De Veirman et al. 2017). Past research finds that influencer marketing has the potential to be an effective subset of digital advertising because influencers' posts are seen as more relatable and more personable than those of celebrities (De Veirman et al. 2017; Hughes et al. 2019; Lou et al. 2019). The appeal of influencers arises from the fact that their content can influence purchase decisions like a celebrity. Simultaneously, their content is relatable and ordinary enough for the average consumer. Hence, their product endorsements are more believable since generally an influencer shares "the personal, usually publicly inaccessible aspects of their life with their followers" (De Veirman et al. 2017). Any product endorsement is accompanied by a personal story; consequently, the influencer's followers are more likely to translate emotional investment into brand engagement, i.e. liking & commenting on a brand's social media channels, and even purchasing the brand's product.

When a brand works with an influencer, its objective is to either (a) maximize brand awareness by tapping into the influencer's social network or (b) get potential consumers to try the product. Hughes et al. (2019) show how hedonic content, especially when it comes to low involvement in the consumer buyer journey, determines whether a potential consumer will be interested in a brand's offer. The theoretical underpinning with regards to the commercial appeal of influencer marketing comes from the principle that with the advent of social media, people "can instead fashion their own autonomously authored brand" (Khamis et al. 2017). Being able to craft a brand around a specific niche allows brands to leverage influencer content reliably in their advertisements because it allows for personalized and consistent messaging. Furthermore, influencer content is not subject to ad blockers since such content is often user generated. The combination of user-generated content in the form of visuals such as photos and videos has been shown to drive greater interest among potential consumers viewing & consuming said content. Additionally, when processing such content in the form of social media posts, consumers engage in "correspondent inferences about the endorser" (Kapitan et al. 2016) which either leads to a mere superficial interaction or a deeper elaboration on part of the consumer.

Taking all these implications into account, one key problem that past research touches on in its discussion of influencer marketing is that brands struggle to identify the appropriate influencers to enlist for a campaign (Lou et al. 2019; Munnukka et al. 2016; de Veirman et al. 2017). Identifying the right influencer for a campaign is critical because it helps the brand assess the overall impact of the influencer's image, positive or negative, and how it is relevant to overall brand perception. Currently, scant research on the interplay exists. However, in the following section, I will discuss how we can use celebrities as a proxy to measure the impact of negative publicity on brands that partner with influencers as a suitable theoretical framework.

How Does Negative Publicity Affect Brand-Influencer Partnerships?

There are two competing theories with respect to how negative publicity affects influencers. In examining existing literature, we can use celebrities as a stand-in for influencers.

Researchers found that the degree of trustworthiness and the degree of credibility are major factors in determining an advertisement's effectiveness (Munnukka et al. 2016). Most research surrounding this phenomenon hinges on how celebrities facing negative publicity affect overall brand perception. Research on negative publicity faced by celebrities suggest that the stronger the association between the celebrity and the brand he/she is promoting, the worse the fallout would be from any negative incident tied to the celebrity (Um et al. 2016; Thwaites et al. 2012; Carrillat et al. 2014). However, these researchers also mention that the extent of the fallout is dependent on the degree of prior brand commitment on the part of the consumer; if a consumer already has a strong commitment to the brand, he/she is less likely to be swayed from not buying the brand's product. Strong brand loyalty means the consumer may be willing to overlook the influencer's faults. Um et al. (2016) show that "people with brand commitment, when exposed to negative celebrity information, showed higher purchase intention than people with low brand commitment." Brand loyalists are therefore more willing to overlook the influencer's mishaps, and still purchase from the brand.

On the other hand, in the event of a negative, public incident, the influencer's mishaps may degrade the moral reputation of the brand in some consumers' eyes. The literature tends to classify consumers into one of two groups: those who have a high brand commitment, i.e. brand loyalists & those who have a low brand commitment, i.e. consumers who will readily switch to another brand. Zhou et al. (2013) identify the factors that put a brand's perception at risk, and all these factors can be attributed to a public, negative incident a celebrity figure/influencer faces. Negative, public incidents often involve some level of degradation of moral character. These researchers found that low commitment consumers are more likely to benchmark a wrongful act the celebrity figure/influencer commits against what the general public would classify as acceptable. They would then extrapolate the celebrity figure's bad behavior to the brand's overall perception which serves as a justification for these consumers to switch to purchasing from a different brand. Taken together, these papers employ a variety of methodologies ranging from scaled questionnaires to experiments on a diverse set of influencer typecast social media profiles.

CONTRIBUTION & HYPOTHESES

Research cannot necessarily extrapolate celebrities to influencers, because influencers are more reminiscent of the average person, despite the elevated social media presence. The influencer's fame is largely attributed to their following whereas a celebrity's fame is largely attributed to external sources besides social media channels such as Instagram. Furthermore, it is not sufficient to conclude that brands should solely focus on the influencers' follower counts in determining partnerships, a limitation that De Veirman et al. (2017) admits. Additionally, there is most likely a noticeable difference in terms of the impact an influencer's public, negative incident has on a brand. That difference arises from the following size. It is arguable that influencers with a following size of greater than or equal to 1,000,000[1] would have an impact comparable to that of a celebrity whereas influencers with a following size of between 100,000 and 1,000,000 would only be affected minimally. To approximate consumers' responses, I chose the Instagram comment section as my source of analysis. Comment sections on social media such as Instagram provide a clear picture of how the influencer's followers and non-followers feel in their interactions with the influencer's posts. In other words, the sentiment of the comments helps me assess the overall personal brand sentiment of the influencer. The researchers in previous literature did not address this discrepancy nor did they analyze actual influencer profiles which is what my research aims to do; below are my hypotheses.

Group H – 'High Following'

In the event of a public, negative incident, influencers with a high following (greater than or equal to 1,000,000 followers) will see a negative shift in personal brand

[1] Social media practitioners concur that a mega-influencer has a following of at least 1 million. The high following group in my research corresponds to the mega-influencer tier (99firms).

sentiment. The personal brand sentiment of influencers in the high following group will be more negative than that of prior to the incident. If there is no public, negative incident, influencers with a high following do not see a shift in personal brand sentiment.

Group L – 'Moderate Following'

In the event of a public, negative incident, influencers with a moderate following (between 100,000 and 1,000,000 followers) may see a negative shift in personal brand sentiment but they will quickly regain the loss in positive personal brand sentiment. The personal brand sentiment of influencers in the moderate following group will stabilize more readily over time than that of influencers in the high following group. If there is no public, negative incident, influencers with a moderate following do not see a shift in personal brand sentiment.

METHODOLOGY

Project Overview

The data consists of aggregated publicly available comments on select influencers' Instagram posts. To determine when the public, negative incident happened, I search the influencer's name on Google Trends; if there is a spike on a specific day, I determine that day to be the event of the incident. To scrape the comments, I used the service, exportcomments.com, which provides me the exact timestamps of the comments in Coordinated Universal Time (UTC), and the comments from each post link inputted. The Instagram users who comment on an influencer's post can consist of either the influencer's own followers or non-followers who are drawn to the influencer's profile because of the public, negative incident. In this study, I define a public, negative incident to be an incident where the influencer's incident is publicized by mass media & mainstream media outlets in such a way that the influencer suffers noticeable negative repercussions, i.e. visible backlash in the comments section, a canceled brand deal, etc. Additionally, those negative repercussions would dent the influencer's overall image.

Since I am interested in assessing the impact of a public, negative incident based on the number of followers an influencer has, I divide the four influencers[2] into two groups based on following size: an influencer who has at least 1,000,000 followers is classified as 'high following, Group H'; an influencer who has between 100,000 and 1,000,000 followers is classified as 'moderate following.'

Methodology

My methodology is similar to De Veirman et al. (2017) 's method where the researchers investigated how the size of an influencer's following impacts brand attitude. They used a 2 x 2 experimental design; I use a 2 x 2 quasi-experimental design to test my hypotheses. My quasi-experiment has a 2 (did the influencer face a public, negative incident: yes or no) by 2 (large following size vs. medium following size) set up. The treatment is the public, negative incident. To test for causation, I chose an influencer who never faced a public, negative incident for each following size group to serve as my control. For each following size group, an influencer who faced a public, negative incident is the treated condition. My unit of analysis consists of aggregated comments per influencer in a specified timeframe which differed between the two following size groups. Refer to **Figure 1** to see a sample of comments from an influencer's Instagram profile.

[2] Links to Instagram profiles - I accessed the data February 2020.
Olivia Jade: https://www.instagram.com/oliviajade/
Lauren Elizabeth: https://www.instagram.com/laurenelizabeth/
MyKenna Jean: https://www.instagram.com/mykenna/
Champagne and Chanel (Emily Herrin): https://www.instagram.com/champagneandchanel/

Figure 1: *Select comments on one of MyKenna Jean's Instagram posts, dated February 3, 2020*

To mitigate issues with internal validity, both the treated influencer's and the control influencer's attributes have to be held constant. The control influencer (no public, negative incident occurred) and the treated influencer (a public, negative incident occurred) will be treated as one pair. Therefore, there will be one such pair in the 'high following' group, and the other pair will be in the 'moderate following group.' As part of an internal validity check, De Veirman et al. (2017) ensured that the mockup Instagram accounts they made had a similar Instagram bio. Furthermore, the researchers verified that the photos created per influencer were at least reminiscent of the other influencer and that the content of these mockup influencers fell in the same niche. Additionally, these mockup influencers would have a similar number of followers given the "number of followers" condition the researchers included in their experiment. I incorporated these checks from De Veirman et al. (2017) into my analysis. An additional check I add for internal validity is ensuring that each pair of treated & control influencers worked with similar brands; this would ensure that brand partnerships are not creating interaction effects in my study.

Moving forward, I will denote the 'high following' group as Group H and the 'moderate following' group as Group L. In the next few sections, I will describe the characteristics of the data I collected from both groups H & L. I intend to use the group name and the size of the influencer's following group interchangeably.

Group H - 'High Following'

As noted earlier, a high following influencer has a following of at least 1,000,000. The experimental influencer of interest is Olivia Jade. She has a following of 1.3 million. There was a noticeable spike in searches for Olivia Jade on March 10, 2019. Google Trends notes that March 10, 2019, is the point in time where 'Olivia Jade' as a search term obtained peak popularity (100). **Figure 2** shows the peak observed on Google Trends.

The spike arose due to a public, negative incident Olivia Jade faced; to briefly explain, Olivia Jade is a prominent influencer who was involved in a nationwide college admissions scandal because she forged photos and documents to be accepted as a competitive rower to the University of Southern California (USC). Multiple media outlets covered the scandal once Olivia Jade's involvement was confirmed, and almost simultaneously, Olivia Jade's Instagram profile was deluged with a barrage of negative comments. Given the hypothesis I described earlier, I suspected that Olivia Jade would see a significant negative shift in personal brand sentiment.

To control for the treated influencer, I included an influencer with a similar following to Olivia Jade who did not face a public, negative incident. Refer to **Figure 2** to see how Google search trends markedly differ between Olivia Jade and Lauren Elizabeth. The control influencer of interest is Lauren Elizabeth who had 1.1 million followers at the time the study was conducted. Lauren Elizabeth's content is also in the fashion & beauty niche, the same niche as Olivia Jade's content. For both influencers, I scraped a total of approximately 3500 comments. The timeframe of the comments collected for both started on the week of January 27, 2019[3], and ended on March 14, 2019. To make the results comparable, I ensured I collected comments within the same timeframe for both the control and experimental influencers.

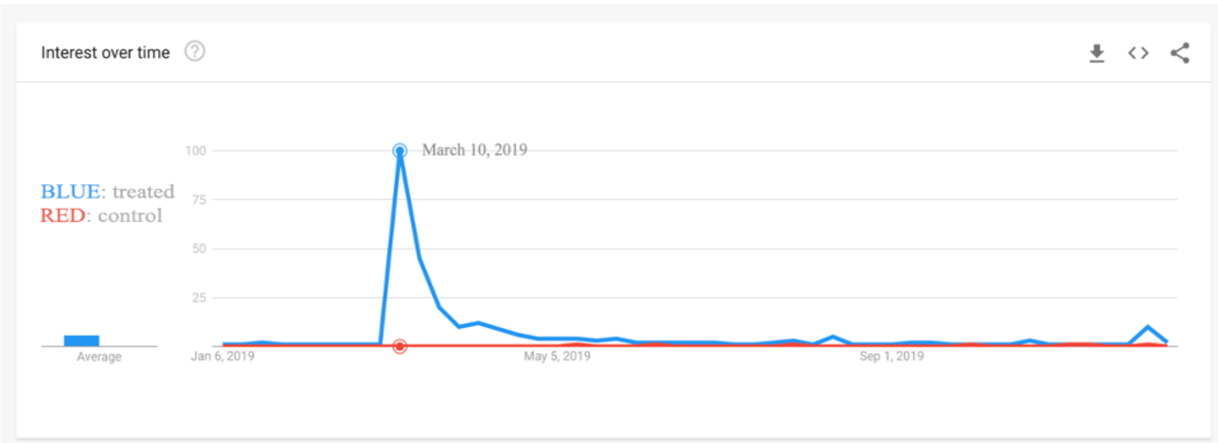


***Figure 2:** Google search trend graph in 2019 - blue is Google keyword "olivia jade", red is Google keyword "lauren elizabeth"*

Group L - 'Moderate Following'

As noted earlier, a 'moderate following' influencer has a following of between 100,000 and 1,000,000. The experimental influencer of interest is MyKenna Jean. She has a following of 298,000. There was a noticeable spike in searches for MyKenna on February 6, 2020. Google Trends notes that February 6, 2020, is the point in time where 'mykenna' as a search term obtained peak popularity (100). **Figure 3** shows the peak observed on Google Trends.

The spike in searches happened because MyKenna was involved in a series of embarrassing incidents on a Bachelor episode that compromised her overall image. The Bachelor is an annual romantic reality TV show based in the US where female contestants engage in various means to woo the Bachelor, the man who is in search of his long-time partner. As such,

[3] High Following Group: Prior to March 10, 2019, average sentiment scores were computed by week. After March 10, 2019, average sentiment scores were computed by day.

various media outlets cover every episode of the Bachelor. Prior to MyKenna's stint on the Bachelor, MyKenna Jean was and is still as of the time of the study, predominantly a fashion & lifestyle influencer. As soon as coverage of the episode broke, some Instagram users left negative comments on MyKenna's posts, albeit the backlash was nowhere comparable to that of Olivia Jade. Given the hypothesis I described earlier, I suspected that MyKenna would see a negative shift in personal brand sentiment, the caveat being that this shift would only be temporary.

To control for the treated influencer, I included an influencer with a similar following to MyKenna Jean who did not face a public, negative incident. The control influencer of interest is Champagne and Chanel (Emily Herren) who had 990,000 followers at the time the study was conducted. Champagne and Chanel's content is also in the fashion & lifestyle niche, the same niche as MyKenna Jean's content. For both influencers, I scraped a total of approximately 9000 comments. The timeframe of the comments collected for both started on January 31, 2020 and ended on February 12, 2020. To make the results comparable, I ensured I collected comments within the same timeframe for both the control and treated influencers. Refer to **Figure 3** to see how Google search trends markedly differ between MyKenna Jean and Champagne and Chanel.

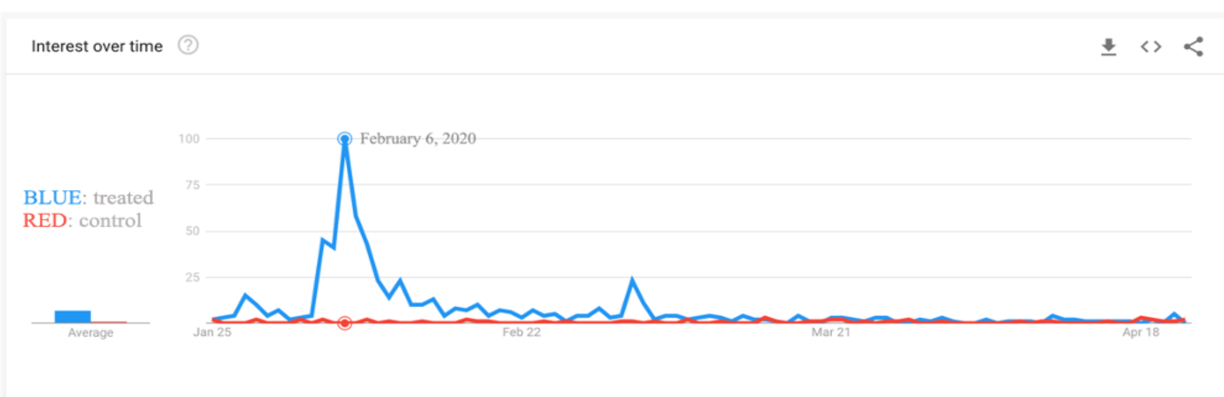


Figure 3: *Google search trend graph from January 25, 2020 to around April 18, 2020 - blue is Google keyword "mykenna", red is Google keyword "champagne and chanel"*

Manipulation in R

I used the syuzhet package in R to attach the sentiment scores to each comment. Each influencer had her own comment .csv file which I read into R. I converted the comments for each of the four influencers into character vectors; then, I used the get_sentiment function to extract the sentiment scores for the comments, using the default method. Additionally, I used the lubridate package in R to convert the dates assigned to the comments I scraped into the day/month/year, hour/minute/second format to allow for easy visualization in Tableau. Using both packages, I revised my comment files for the four influencers to include a 'score' column for the sentiment scores and a 'time' column with the new date formats. I then resaved the files into updated .csv files for the influencers. Refer to **Figure 4** for a snapshot of the R code used. Refer to **Figures 5 & 6** for an example of a positive sentiment comment, and an example of a negative sentiment comment respectively.

```
laurene <- read.csv("~/Desktop/laurene_comments.csv")
laurene$Comment <- as.character(laurene$Comment)
laurene$Score <- get_sentiment(laurene$Comment)
laurene$Time <- dmy_hms(laurene$Date)
write.csv(laurene, 'laurene.csv')
```

Figure 4: *R code for the 'high following' control influencer, Lauren Elizabeth - duplicated key parts of the code for the other influencers*

```
> get_sentiment("Happy birthday!! Cheers to making each year count fellow Canadian")
[1] 2.95
```

Figure 5: *Instagram comment with positive sentiment score, comment is from MyKenna Jean's post-dated February 3, 2020*

```
> get_sentiment("your brand is dead and done. bye.")
[1] -1
```

Figure 6: *Instagram comment with negative sentiment score, comment is from Olivia Jade's post-dated December 8, 2018*

RESULTS

General Summary Statistics & Scatterplots

Summary statistics for the high following group (Group H) are shown in **Table 1**, and summary statistics for the moderate following group (Group L) are shown in **Table 2**.

	OVERALL SENTIMENT SCORE MEAN	PRE-MARCH 10 SENTIMENT SCORE MEAN	POST- MARCH 10 SENTIMENT SCORE MEAN	SENTIMENT SCORE STANDARD DEVIATION	NUMBER OF OBSERVATIONS
CONTROL	0.241	0.254	0.198	0.536	1720
TREATMENT*	-0.164	0.135	-0.175	1.139	1742

Table 1[4]*: Summary statistics for the high following group - control is Lauren Elizabeth, treatment is Olivia Jade*
**Public, negative incident happened on March 10, 2019.*

	OVERALL SENTIMENT SCORE MEAN	PRE- FEB 6 SENTIMENT SCORE MEAN	POST- FEB 6 SENTIMENT SCORE MEAN	SENTIMENT SCORE STANDARD DEVIATION	NUMBER OF OBSERVATIONS
CONTROL	0.446	0.384	0.535	0.511	3967
TREATMENT*	0.509	0.559	0.482	0.856	4746

Table 2[5]*: Summary statistics for the moderate following group - control is Champagne and Chanel, treatment is MyKenna Jean*
** Public, negative incident happened on February 6, 2020.*

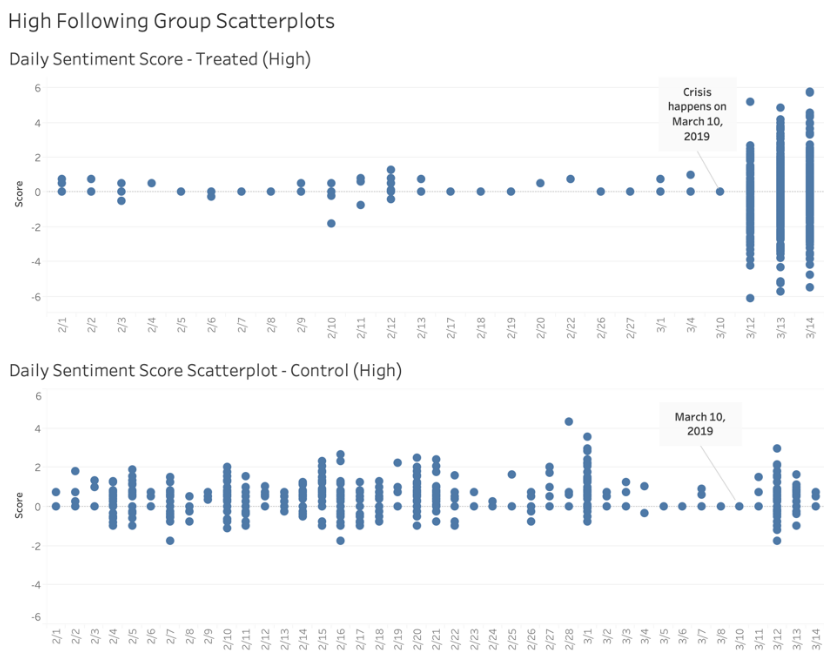
Refer to **Figure 7** for the sentiment score scatterplots of each following group: high following group (Group H) and moderate following group (Group L). Both the control and treated within each following group are plotted. Each point denotes a sentiment score per comment. The sentiment scores are plotted on a daily basis.

[4]Prior to March 10, 2019, Olivia Jade in aggregate received 63 comments. After March 10, 2019, Olivia Jade in aggregate received 1679 comments. Given the scale of the public, negative incident which was a college admissions scandal, it is not surprising that Olivia Jade had a plethora of comments post-March 10, 2019.

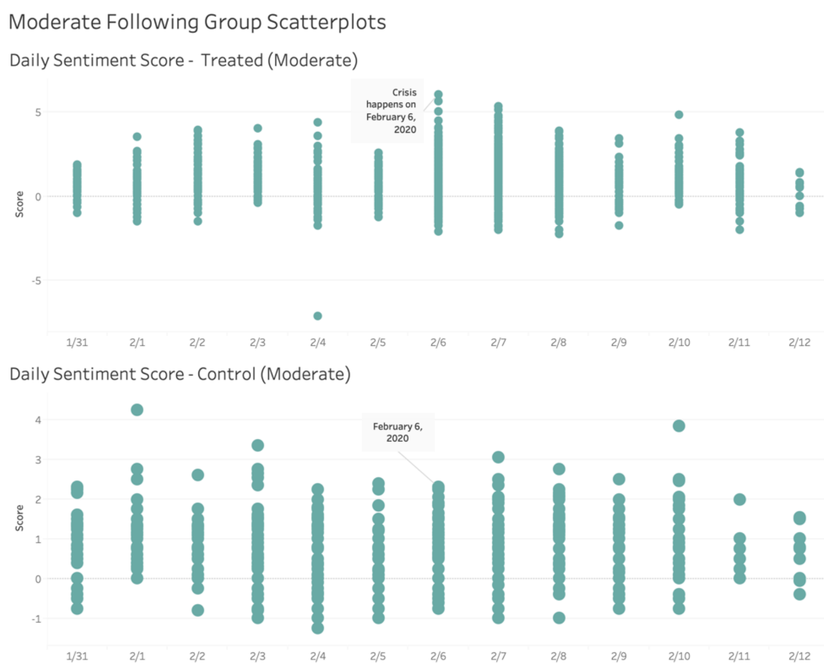
Prior to March 10, 2019, the control influencer, Lauren Elizabeth in aggregate received 1326 comments. After March 10, 2019, Lauren Elizabeth in aggregate received 394. For an influencer with no public, negative incident, 394 is a reasonable number of comments across 4 days since the influencer's followers may not comment on her post the same day it is posted.

[5] Prior to February 6, 2020, MyKenna Jean in aggregate received 1662 comments. After February 6, 2020, MyKenna Jean in aggregate received 3084 comments. MyKenna Jean received much more comments post-incident.

Prior to February 6, 2020, the control influencer, Champagne and Chanel in aggregate received 2342 comments. After February 6, 2020, Champagne and Chanel in aggregate received 1625. The number of comments between the two periods is distributed similarly to that of Lauren Elizabeth. For an influencer with no public, negative incident, 1625 is a reasonable number of comments across 6 days since the influencer's followers may not comment on her post the same day it is posted.



Scatterplot of Treated (Olivia Jade's) sentiment scores) & Control (Lauren Elizabeth's) sentiment scores



Scatterplot of Treated (MyKenna Jean's) sentiment scores & Control(Champagne and Chanel's) sentiment scores
Figure 7: *Scatterplots of influencers' sentiment scores for each following group (daily scores)*

Below I will describe the average sentiment score graphs of each following group, high following and moderate following. The results will be divided based on the following size.

Average Sentiment Scores Trend

Group H- 'High Following'

As noted earlier, the event of interest, the public, negative incident happened on March 10, 2019. I delineate March 10, 2019 as the cutoff point to distinguish between dates before March 10, 2019, and dates after March 10, 2019. I apply the same process for my control influencer, Lauren Elizabeth as I do for my treated influencer, Olivia Jade. To see a trend between pre- March 10 and post - March 10, I graph average weekly & daily sentiment scores from the week of January 27, 2019 to March 14, 2019. Prior to March 10, 2019, the average sentiment scores are computed by week[6], and after March 10, 2019, the average sentiment scores are computed by day. I plot average sentiment scores for both my control influencer and my treated influencer. Refer to **Figure 8** for the average sentiment score trends of both Olivia Jade (treatment) and Lauren Elizabeth (control)[7].

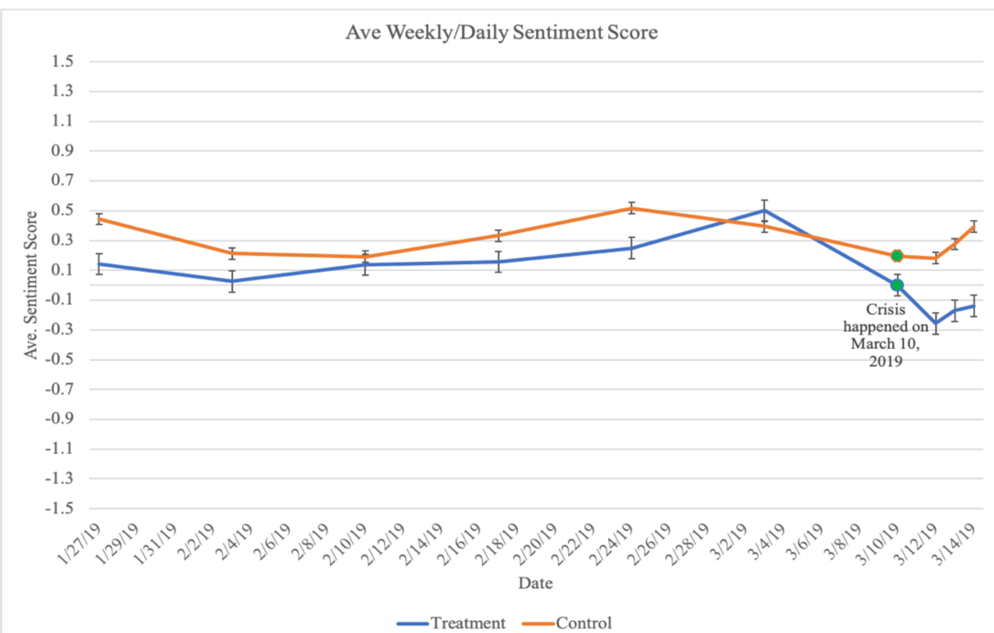


***Figure 8**: Treated (Olivia Jade) & Control (Lauren Elizabeth) average sentiment score trends – averages computed by week prior to March 10, 2019 & averages computed by day after March 10, 2019*

[6] Before March 10, 2019, which is when the public, negative incident happened, there was an accumulation of comments for both influencers, Olivia Jade, and Lauren Elizabeth. In my later analysis, I compute the weekly average sentiment scores. However, data in a comparable timeframe after March 10, 2019 is limited, because the latest date for which I could scrape comments was March 14, 2019. This is because Olivia Jade disabled comments after March 14, 2019.

[7] A sentiment score of 0.0 implies a neutral tone. For all average sentiment score graphs, 0.0 is my baseline.

Prior to March 10, 2019, the trend for the control influencer shows that the average sentiment was positive, hovering between the baseline, 0.0 and 0.5. After the cutoff date, the average sentiment for Lauren Elizabeth was still positive. For Lauren Elizabeth, no public, negative incident occurred, so I expected the average comment sentiment to remain relatively stable between pre-March 10, 2019, and post-March 10, 2019.

Prior to March 10, 2019, the trend for the treated influencer shows that the average sentiment was positive, hovering between the baseline, 0.0 and 0.5. This finding implies that the comments prior to March 10, 2019, on Olivia Jade's Instagram were slightly positive. On the other hand, after March 10, 2019, the graph shows that there is a marked dip in sentiment. Now, the average sentiment falls between the baseline, 0.0 and -0.5. In fact, the curve flattens below 0.0 which shows that the new normal for comment sentiment on Olivia Jade's Instagram profile is expected to remain negative for some period of time. Granted, had Olivia Jade not disabled Instagram comments for the general public, we would continue to see a sustained decrease in the average sentiment of comments. Most of the error bars on **Figure 8** for both groups are small which suggests that the majority of daily average comment sentiments are close to the true values for both the control and the treated.

Group L - 'Moderate Following'

As noted earlier, the public, negative incident happened on February 6, 2020. I delineate February 6, 2020 as the cutoff point to distinguish between dates before February 6, 2020, and dates after February 6, 2020. I apply the same process for my control influencer, Champagne and Chanel as I do for my treated influencer, MyKenna Jean. To see a trend between pre-February 6 and post-February 6, I graph average daily sentiment scores from January 31, 2020 to February 12, 2020. Prior to February 6, 2020, the average sentiment scores are computed by day, and after February 6, 2020, the average sentiment scores are computed by day. I plot average sentiment scores for both my control influencer and my treated influencer. Refer to **Figure 9** for the average sentiment score trends of both MyKenna Jean (treatment) and Champagne and Chanel (control) respectively.

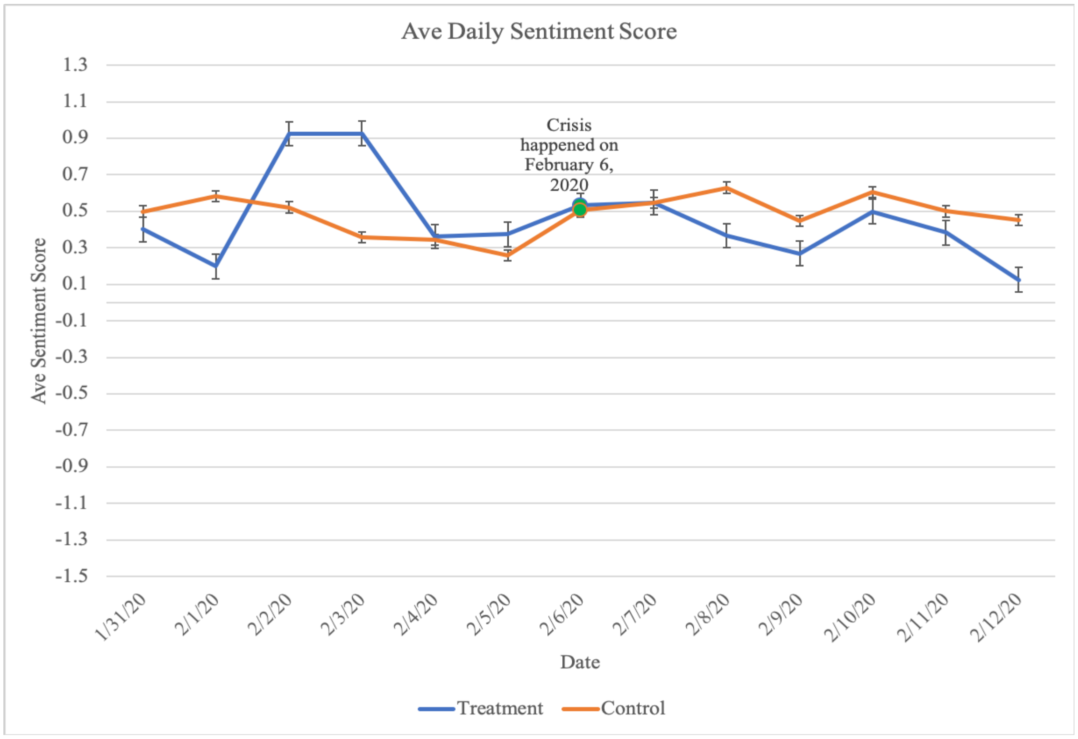


***Figure 9**: Treated (MyKenna Jean) & Control (Champagne & Chanel) average sentiment score trends - averages computed by day prior to February 6, 2020 & averages computed by day after February 6, 2020*

Prior to February 6, 2020, the trend for the control influencer shows that the average sentiment was positive, hovering between the baseline, 0.0 and 0.5. After the cutoff date, the average sentiment for Champagne & Chanel was still positive. For Champagne & Chanel, no public, negative incident occurred, so I expected the average comment sentiment to remain relatively stable between pre-February 6, 2020, and post-February 6, 2020.

Prior to February 6, 2020, the trend for the treated influencer shows that the average sentiment was positive, hovering between the baseline, 0.0 and 0.5. At times, the average sentiment exceeded 0.5, as plateau covering February 2 & 3, 2020 indicates. This finding implies that the comments prior to February 6, 2020, on MyKenna Jean's Instagram were slightly positive. On the other hand, after February 6, 2020, the trend shows that there is a dip in average comment sentiment; however, the average comment sentiment for the days after is still positive. Yet, there is a slight decrease in average sentiment post-incident, but the decrease is not as noticeable as that of the treatment influencer in the high following group. The new normal for the treatment influencer in the moderate following group is still positive despite a slight decrease in daily average sentiment. Most of the error bars on **Figure 9** for both groups are small which suggests that the majority of daily average comment sentiments are close to the true values for both the control and the treated.

For each following group, I then ran a difference in differences analysis to test for significance between the treated influencer and the control influencer. Additionally, I ran a second difference in differences analysis to test for significance between the following groups. Prior to running both analyses, I will demonstrate that both following groups adhere to the parallel trends assumption.

Difference in Differences Analysis - Per Following Group

Parallel Trends Assumption

Pre-period, the average comment sentiment scores for both the control influencer and the treated influencer in the high following group follow a similar trajectory. Post-period, the average comment sentiment scores for both groups diverge; the average comment sentiment score for the treated influencer remains negative whereas the average comment sentiment score for the control influencer becomes increasingly positive. From this preliminary analysis, I am confident that the public, negative incident caused the post-period difference. **Figure 10** shows the pre-period and post-period trajectories of both the control and treated influencer(s) in the high following group.

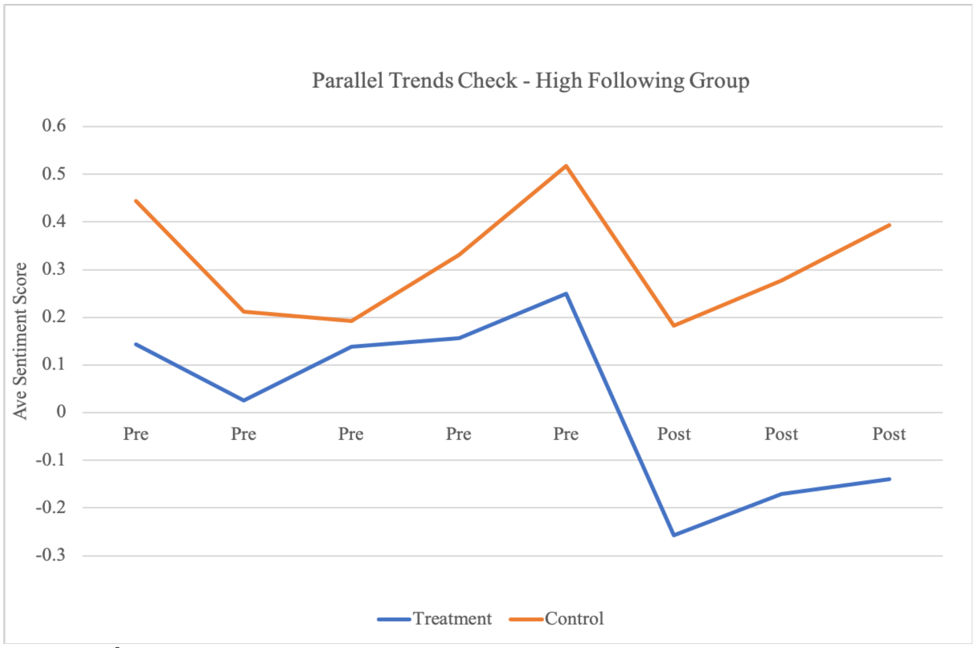


Figure 10*[8]*: Parallel Trends Check for High Following Group

Pre-period, the average comment sentiment scores for both the control influencer and the treated influencer in the moderate following group follow a similar trajectory in that the average comment sentiment scores for both groups are within the same score range. The pre-period lines of both groups do in fact intersect. Post-period, the average comment sentiment scores for both groups diverge; the average comment sentiment score for the treated influencer while still positive continuously decreases to below a score of 0.3 whereas the control influencer has a higher average comment sentiment score. **Figure 11** shows the pre-period and post-period trajectories of both the control and treated influencer(s) in the moderate following group.

[8]The points denoted as pre-period are weekly average comment sentiments. The points denoted as post-period are weekly average comment sentiments.

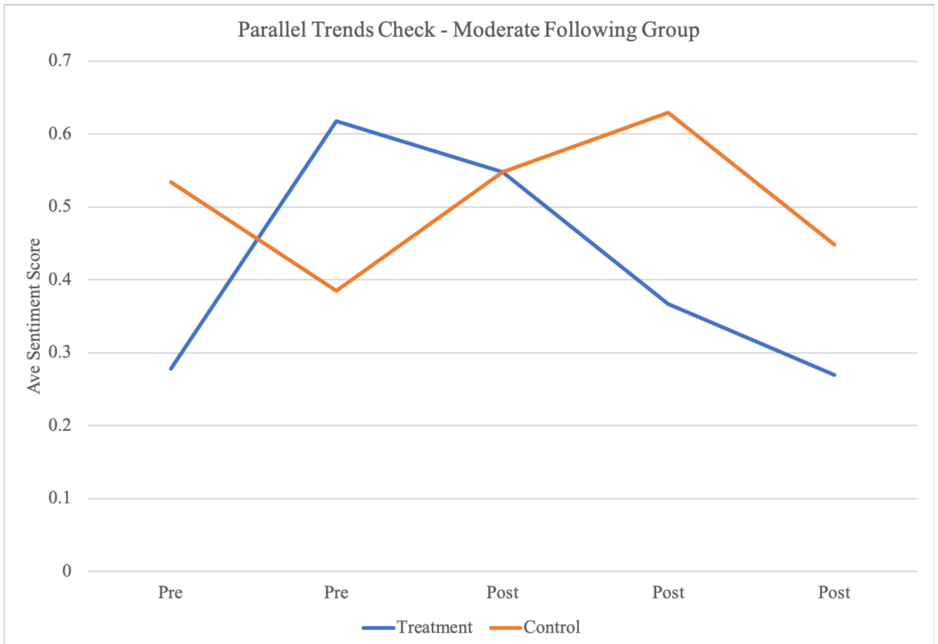


Figure 11*[9]*: Parallel Trends Check for Moderate Following Group

Group H – 'High Following'

I ran a difference in differences analysis to assess whether the difference in means is statistically significant between the treatment (Olivia Jade) and the control (Lauren Elizabeth). The results are summarized in **Figure 12**.

```
Call:
lm(formula = grouph$Score ~ grouph$Time + grouph$Treatment +
    grouph$did)

Residuals:
    Min      1Q  Median      3Q     Max
-5.9253 -0.2546 -0.1753  0.4247  5.9247

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.25460    0.02446  10.407   <2e-16 ***
grouph$Time      -0.05803    0.05111  -1.135   0.2563
grouph$Treatment -0.11968    0.11487  -1.042   0.2975
grouph$did       -0.25161    0.12522  -2.009   0.0446 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8908 on 3458 degrees of freedom
Multiple R-squared:  0.0514,    Adjusted R-squared:  0.05057
F-statistic: 62.45 on 3 and 3458 DF,  p-value: < 2.2e-16
```

Figure 12[10]*: R output for difference in differences analysis - Group H*

[9] The points denoted as pre-period are weekly average comment sentiments. The points denoted as post-period are weekly average comment sentiments.
[10] Time is dummy variable for pre-incident (0) & post-incident (1). Treatment is dummy variable for control (0) & treatment (1). 'did' is the interaction term: Treatment * Time. I replicated this R code for the other following group, group L.

Since the p-value of 0.0446 is less than the alpha value of 0.05, the difference in means between the two groups is statistically significant. Furthermore, a negative ‘difference in differences (did)’ coefficient of -0.252 suggests that the treatment has a statistically significant, negative effect on average comment sentiment. In other words, post-incident, the treated influencer’s (Olivia Jade) average comment sentiment is expected to drop.

Group L – ‘Moderate Following’

I ran a difference in differences analysis to assess whether the difference in means is statistically significant between the treatment (MyKenna Jean) and the control (Champagne and Chanel). The results are summarized in **Figure 13**.

```
Call:
lm(formula = groupl$Score ~ groupl$Time + groupl$Treatment +
    groupl$did)

Residuals:
    Min      1Q  Median      3Q     Max
-7.7085 -0.4824 -0.0585  0.3176  5.5676

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.38373    0.01484  25.864  < 2e-16 ***
groupl$Time       0.15116    0.02318   6.521 7.39e-11 ***
groupl$Treatment  0.17481    0.02303   7.591 3.50e-14 ***
groupl$did       -0.22734    0.03186  -7.137 1.03e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.718 on 8709 degrees of freedom
Multiple R-squared:  0.008145,	Adjusted R-squared:  0.007804
F-statistic: 23.84 on 3 and 8709 DF,  p-value: 2.326e-15
```

Figure 13[11]: R output for difference in differences analysis – Group L

Since the p-value of 1.03 e-12 is less than the alpha value of 0.05, the difference in means between the two groups is statistically significant. Furthermore, a negative ‘difference in differences (did)’ coefficient of -0.227 suggests that the treatment has a statistically

[11] Time is dummy variable for pre-incident (0) & post-incident (1). Treatment is dummy variable for control (0) & treatment (1). ‘did’ is the interaction term: Treatment * Time. I replicated this R code for the other following group, group H.

significant, negative effect on average comment sentiment. In other words, post-incident, the treated influencer's (MyKenna Jean) average comment sentiment is expected to drop.

Difference in Differences Analysis - Aggregate

To explore whether the moderate following (L) - treated group sees less of a negative effect than the high following (H) - treated group, I ran a difference in differences analysis with an extra dummy variable for following. I coded 1 for the high following group (H) and 0 for the moderate following group (L). I substituted the previous 'difference in differences (did)' interaction for a new one, inclusive of the 'following' dummy variable. The results are summarized in **Figure 14.**

```
Call:
lm(formula = aggregate$Score ~ aggregate$Time + aggregate$Treatment +
    aggregate$Following + aggregate$did)

Residuals:
    Min      1Q  Median      3Q     Max
-7.6433 -0.4933 -0.0933  0.3067  5.9247

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.43937    0.01386  31.694  < 2e-16 ***
aggregate$Time       0.02115    0.01592   1.329  0.18400
aggregate$Treatment  0.05394    0.01679   3.213  0.00132 **
aggregate$Following -0.20840    0.02199  -9.478  < 2e-16 ***
aggregate$did       -0.48077    0.03193 -15.056  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7726 on 12170 degrees of freedom
Multiple R-squared:  0.08109,   Adjusted R-squared:  0.08078
F-statistic: 268.5 on 4 and 12170 DF,  p-value: < 2.2e-16
```

Figure 14[12]*: R output for difference in differences analysis – Group L*

Since the p-value of <2e-16 is less than the alpha value of 0.05, the difference in means between the two following groups is statistically significant. Furthermore, a negative 'difference in differences (did)' coefficient of -0.481 suggests that the effect of the treatment on the high following group has a more statistically significant, negative impact on average comment

[12]Time is a dummy variable for pre-incident (0) & post-incident (1). Treatment is a dummy variable for control (0) & treatment (1). Following is a dummy variable for high-following (1) & low-following (0) . 'did' is the interaction term: Treatment * Time * Following. I replicated this R code for the other following group, group H.

sentiment than that of the moderate following group. In other words, while the average comment sentiment post-incident drops for the treated influencer in the moderate following group, there is less of a negative effect than for the treated influencer in the high following group.

DISCUSSION

Theoretical Contributions

My study aims to establish a theoretical framework which explains the effect of a public, negative incident on how audiences perceive influencers based on the size of the influencers' following. Currently, there is no existing theory on how an influencer's following size impacts perception of the influencer. My research does however draw on existing perception theories pertaining to celebrities; for one, the degree of trustworthiness and the degree of credibility are cited as major factors in determining the effectiveness of the influencer's post. My findings suggest that it is easy for an influencer with either a high following or a moderate following to jeopardize trustworthiness and credibility in the event of a public, negative incident. As existing literature has noted, a public, negative incident shatters an influencer's curated image by bringing unsavory qualities and traits to light. The exposure of this degradation in moral character therefore calls the influencer's image into question which deteriorates its believability.

Generally, one explanation is that the influencer's following in addition to the non-followers are actively monitoring the influencer's actions. Hence, the repercussions will be more severe and longer-lasting as overall sentiment drops post-incident. When a brand partners with an influencer with a high following, the brand is at increased risk of having the loss of trustworthiness and credibility translate to its own image. In my research, I find that this conclusion also holds true to some degree for an influencer with a moderate following. The difference lies in that an influencer with a moderate following who faces an incident will not be as adversely affected as an influencer with a high following who also faces an incident. Nonetheless, an influencer regardless of his/her following size will be affected, because a public, negative incident is generally well-documented, and hence his/her actions post-incident will be under further scrutiny.

Managerial Implications

For social media practitioners, this study reveals the pitfalls of relying on a single influencer with either a high following or a moderate following to promote brands, and the necessity of vetting influencers for brand campaigns. The implications of a public, negative incident have the potential to impact a brand's image severely since the brand will face the same level of scrutiny and criticism the influencer did. To mitigate brand perception risk, social media practitioners should opt to increase the number of influencers they work with, such that a single influencer does not become the sole face of the brand. A brand campaign that features a multitude of influencers will also have the consequence of achieving higher reach since the brand would be able to pull from multiple influencer communities[13]. Based on the results of my analysis, a brand should immediately drop an influencer with a high following who faces a public, negative incident. For an influencer with a moderate following, the brand should scrutinize the development of the public, negative incident. Taking these actions will decrease the likelihood of a significantly negative influencer-brand association.

Limitations

First, I tested a limited sample size; there were only two influencers in the control group and two influencers in the treated group. Future research could expand to more influencers.

[13] Influencer communities is another way of referring to an influencer's following. Generally, influencers who are engaged with their audiences have their own communities.

Second, the public, negative incident could be related to the higher/increasing sentiment in the pre-period. The media could have watched both Olivia Jade (high following) and MyKenna Jean (moderate following) more closely given that their general sentiment was increasing pre-incident. In that context, my study is subject to endogeneity threats. Additionally, the focus of my research was limited to several niches: fashion & lifestyle. It would be interesting to see whether my findings would hold in other niches such as food and fashion. I only analyzed Instagram since it is considered to be the most dominant social media platform for influencer marketing. However, future studies can explore other social media platforms as well as cross-platform interactions to examine whether this phenomenon holds true. Additionally, I did not actively manipulate any variables since I conducted a quasi-experiment.

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